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Explicit forward gait prediction using parametric trajectories adaptation

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Abstract

Performing a subject specific and accurate predictive numerical gait simulation can be of great help in many clinical tasks. Though predictive methods often take into account the modifications applied to a reference motion, they are not always able to include the characteristics and the stability of the predicted motion. We propose an optimization-based approach that includes the resulting characteristics of the predicted motion. The optimization is enhanced by the use of parametric curves to represent the motion trajectories. Experimental studies on subjects with different gait patterns confirmed that our method preserves the characteristics of the gait.

CCS Concepts

•***Computing methodologies*** → ***Physical simulation; Interactive simulation; Optimization algorithms; Control methods;*** •***Applied computing*** → *Health informatics;*

1. Introduction

Computer-aided predictive simulation makes it possible to test a wide diversity of gait scenarios on a numerical human representation. With improvements on accuracy and patient specificity such simulation can nowadays be used in clinical procedure. This study aims at predicting gaits with emphasis on the conservation of a patient specificity. We make the distinction between patient specificities related to its musculoskeletal model and specificities due to additional factors (e.g. footwear, pain, chronic disease).

Broadly speaking, we can identify two categories of approaches: the implicit approach and the explicit approach. In the implicit approach, a control optimal problem is solved. The dynamics of the system is turned into a set of constraints and an objective function is defined. The states and control signals are the unknowns. While the forward explicit approach uses an adaptive system to produce the control signals, and then the system dynamics is integrated. Methods based on implicit approaches can achieve predictions with a good accuracy and in a limited amount of time, but they are not suited for interactive simulation [FSD*19]. Most forward explicit methods obtain predictive motions from the tracking of a modified reference motion [LPLL19]. We propose a different approach for the search of the modifications. Our method uses an optimization of a cost function that includes the evaluation of the simulated motion. Running such optimization-based simulation is a time-consuming routine. To overcome this shortcoming, we reduce the search space by leveraging a parametric representation of the reference motion and knowledge on the simulated gait pattern.

2. Method

2.1. Explicit forward simulation

Our explicit forward predictive simulator uses a skeletal model placed within a physics-based virtual environment and actuated by an adaptive system. This adaptive system generates appropriate control signals to maintain balance, to produce a motion similar to a reference motion and to ensure additional tasks such as minimizing the cost of transportation. At each time step, hypothetical servo-motors placed at each degree of freedom of the model receive signals from the adaptive system. Once the signals are converted into angular moments, the system dynamics is integrated by the physics engine.

Our adaptive system is based on a neural network and stable proportional derivative controllers (SPDC) for each degree of freedom of the virtual character. The input of each SPDC is the sum of an open-loop angular target and an adaptive correction. The open-loop angular target is evaluated from the kinematics of one reference gait cycle. The adaptive correction is computed by the neural network from the current pose of the character and the current percent of gait cycle denoted as ϕ.

The neural network is trained to maintain balance using a data-driven approach. Our goal is to learn a control strategy that produces motions that are similar to the reference kinematics. The cost function is composed of a weighted combination of terms computed from the difference between the current and the reference model's state. An additional term aggregates the sum of the angular moments, to reflect the cost of transportation. We hypothesis that training the neural network on more than one reference kinematics will make it more robust to variations on the reference input, and therefore will allow for prediction.

We first processed the raw kinematics data by rotating the motion to have every mean heading of each motion clip in one direction and setting $\phi = 0$ on the first right foot contact. This way the neural network will not be specialized for a particular walking direction and timing. In the first set, the initial condition ($C0$), a subject walked normally at a self selected speed. In the second set, the altered condition ($C1$), a subject walked also at a self selected speed but was wearing a restrictive brace on the right knee, thus imposing a stiff-knee gait. The restriction was set to 20 degrees of flexion.

2.2. Gait predictions

Once the neural network is trained, the reference kinematics data can be modified to obtain new motions. Predictive motions are thus found by searching sets for modifications that produce valid simulations. The quality of the predictive simulations is measured with an objective function composed of a weighted combination of two terms. The first term estimates the relevancy of the produced motion by penalizing simulations for which the virtual character falls or collisions occur between the legs during the first 15 gait cycles. The second term depends on the targeted gait characteristics. In our example, the stiff-knee gait, it penalizes the knee flexion, measured over the last 10 gait cycles.

Each simulation takes about $1s$ to execute (20 times faster than real-time). It was important to use a method that converge with a minimum number of evaluation and without the need to evaluate gradients because the problem is discontinuous. We chose the Covariance Matrix Adaptation Evolution Strategies (CMA-ES) method as our optimization process [Han07].

With the discrete representation of the motion, there are more than 1000 parameters to optimize. CMA-ES shows best performance with less than 100 parameters so two strategies were used to reduce the search space. First, we compute a parametric approximation of each joint trajectory of the kinematics data, allowing us to model a full trajectory from few control points only. Then, a visual comparison between trajectories from both conditions $C0$ and $C1$ and knowledge from gait analysis of the targeted pattern is used to identify a subset of the trajectories to include in the optimization.

2.3. Parametric trajectories representation

We were looking for a parametric description of the trajectories with the following features : accurate approximation with a small number of parameters, C^2 continuity and fast evaluation. Non-Uniform Rational Basis Spline (NURBS) presents theses advantages. We choose to use cubic periodic NURBS for all trajectories except for the transverse plan pelvis coordinates. For those coordinates we chose cubic B-splines. The optimum placement of the control points was computed as a weighted combination of terms relative to similarity, relative control points placement and weight distribution. Relative control points placement is used to ensure C^2 continuity as cubic NURBS will lose this property if two or more control points have the same x-axis coordinate.

The similarity term is computed as the sum of normalized square residuals between the original data and the NURBS evaluation, for each frame of the original trajectories. The other terms are respectively computed as the minimum distance between two consecutive control points, the mean value of the weights, and the minimum of the weights. We use the CMA-ES method for the optimization as the problem presents discontinuities.

First, we chose to exclude modifications of the transverse plan pelvis coordinates because maintaining C^2 continuity would be unnecessarily complex. Then, for each NURBS control point there are 3 parameters: the x-axis coordinate, the y-axis coordinate and the weight. The search space reachable by modification of the trajectories is reduced by preventing to modify all parameters, but modifying only the y-axis coordinate allows us to maintain the C^2 continuity and does not reduce much the search space compared to the only modification on x-axis or on the weight. Moreover, having only one parameter per control point increases the complexity of the prediction search as low as possible.

3. Results

Effect of multiple gait training When the neural network is trained on one kinematics reference data of the $C0$ set, it is not able to produce stable motions for other reference data of the same set. On the other hand, if the training is performed using all reference data from the set, the trained neural network is able to produce stable motions for all of them.

Parametric trajectories representation We designed our parametric trajectories with 8 control points per NURBS and 20 control points per B-Splines. The error due to this representation was computed as the normalized square residuals between the original discrete values and the evaluations of the parametric trajectories. The mean angular error was 0.37×10^{-3} degrees and the mean position error was 5.3 millimeters (see Table 1).The approximation of the pelvic antero-posterior position has a large error compared to the other approximations but this degree of freedom has larger variation during the cycle.

Reduction of the search space Using our parametric trajectories we still have 152 parameters to optimize. With knowledge from literature on the stiff-knee gait pathology [LOW12,KFRR00,IKS*12, SPRHW08] and analysis of the $C0$ and $C1$ sets we chose to select the following trajectories to reduce the search space to 44 parameters : pelvic obliquity, pelvis height, lumbar bending, hip abduction (left and right legs) and knee flexion (right swing leg). Details on the trajectories are given in Table 2.

Prediction of stiff-knee gaits We use the neural network trained with the complete set of $C0$ gaits. The target maximum right knee flexion was set to the value observed in the $C1$ condition.

The optimization successfully found a set of modifications that match the constraints. To assess the advantage of the simulation-based optimization we analyze 100 simulations generated with var-

Table 1: Mean errors and standard deviations per joint over 16 reference motions. * trajectories have been represented with B-Spline. When two values are given, the first one refers to the left side and second one to the right side.

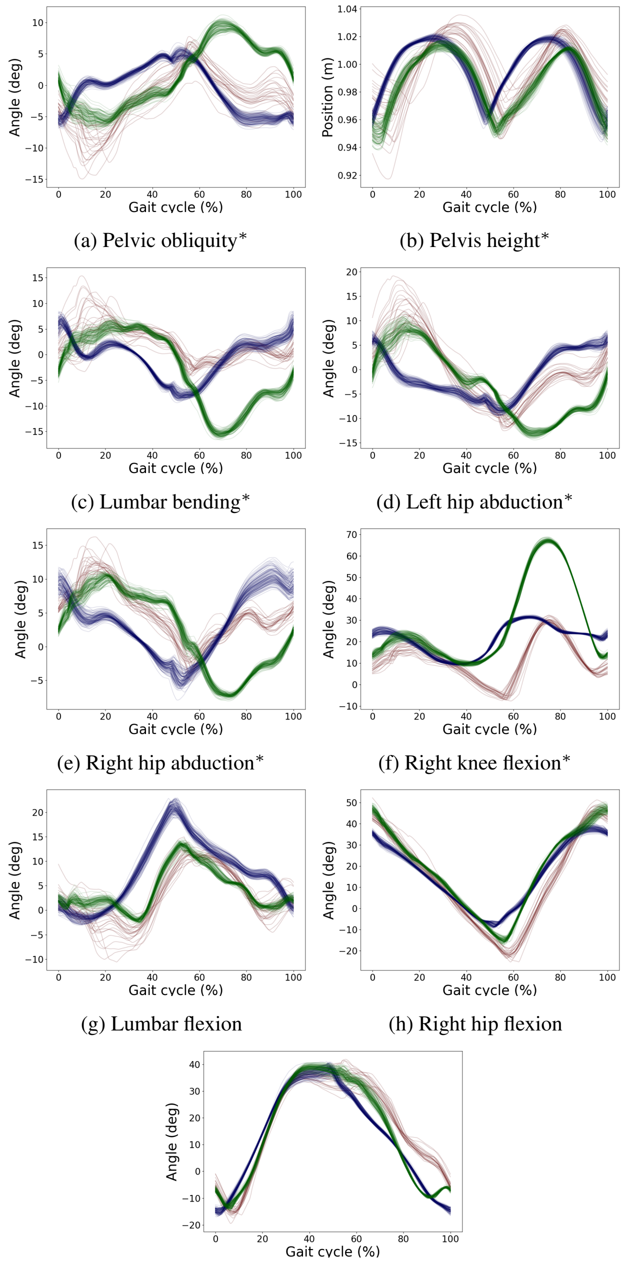
Degree of freedom	Mean errors (10^{-3})		Standard dev. (10^{-3})	
Pelvic obliquity (deg)	0.075		0.046	
Pelvis rotation (deg)	0.031		0.017	
Pelvis sagital angle (deg)	0.29		0.19	
Pelvis antero-posterior* (mm)	16		2.7	
Pelvis height (mm)	0.056		0.039	
Pelvis transversal* (mm)	0.058		0.026	
Lumbar bending (deg)	0.098		0.047	
Lumbar rotation (deg)	0.36		0.19	
Lumbar flexion (deg)	0.32		0.2	
Hip abduction (deg)	0.15	0.15	0.09	0.087
Hip rotation (deg)	0.81	1.2	0.44	1.3
Hip flexion (deg)	0.42	0.51	0.22	0.34
Knee flexion (deg)	0.16	0.16	0.03	0.069
Ankle dorsiflexion (deg)	0.97	0.72	0.78	0.69
Foot eversion (deg)	0.095	0.12	0.062	0.16

Table 2: Results from the comparison between $C0$ and $C1$: o means an observed difference, l means that the literature reports a difference and $*$ indicates if selected for optimization. When two values are given, the first one refers to the left side and second one to the right side.

Degree of freedom	Right swing leg		Right stance leg	
Pelvic obliquity	$ol*$		$o*$	
Pelvis rotation	o		–	
Pelvis sagital angle	–		o	
Pelvis height	$l*$		$o*$	
Pelvis transversal	–		–	
Pelvis antero-posterior	–		–	
Lumbar bending	$o*$		$o*$	
Lumbar rotation	–		–	
Lumbar flexion	–		–	
Hip abduction	$ol*$	$ol*$	$o*$	$o*$
Hip rotation	–	–	–	o
Hip flexion	–	–	–	–
Knee extension	o	$ol*$	o	–

ious starting ϕ. The starting ϕ was randomly selected with maximum variation of 2% from the one used during the optimization process.

On Figure 1, we observe that the simulated kinematics has been affected by the modifications of the reference motion. Dispersion between simulated kinematics increased and is more pronounced during the first half of the swing phase of the right leg ($\phi < 25\%$). The mean value of the simulated kinematics has significantly changed for many degrees of freedom even for the trajectories that were not included in the optimisation. The left hip flexion



(a) Pelvic obliquity* (b) Pelvis height*
(c) Lumbar bending* (d) Left hip abduction*
(e) Right hip abduction* (f) Right knee flexion*
(g) Lumbar flexion (h) Right hip flexion
(i) Left hip flexion

Figure 1: Joint kinematics during the 13^{th} gait cycle. Green curves are $C0$, blue curves are $C1$ and red curves are predictions. * Reference trajectories have been modified by optimization.

(Fig. 1i) during the second half of the stance phase of the right leg ($75\% < \phi < 100\%$) is an example. The mean value of the simulated kinematics has consistently shifted towards the value observed in the $C1$ condition.

We notice that the constraint on the right knee is satisfied for all the 23 tested and successful predictions but a hyperextension is observed at right toes-off (Fig. 1f).

4. Conclusion

We propose a method for predictive simulation of human gaits based on the optimization of an objective function including the evaluation of the simulated motion. Simulation are obtained from modifications of reference kinematics data. A reduction of the search space is used to compensate for the computational cost of the simulations. This reduction is achieved with a parametric representation of the kinematics data and with the selection of a subset of trajectories. Knowledge about the simulated gait pattern is used to select trajectories. Using the proposed method, we were able to produce stable predictions for a stiff-knee gait with significant severity.

Future works will have two objectives : to increase the flexibility of the optimization process and to reduce the dispersion between the predicted kinematics data. The flexibility could be increased by finding the optimal number of control points for each degree of freedom. This will also reduce the size of the search space and allow us to include additional parameters in the optimization process.

Acknowledgments

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